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Simulation for Passengers Convenience using Actual Bus Traffic Data

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Chapter 1
Simulation for Passengers Convenience using Actual Bus Traffic Data

Abstract Public transport bus service is an important means of transportation for commuting, schooling and daily life. However, many unpredictable problems arise, resulting in delays caused by traffic congestion or an increased number of passengers. Changing the operation schedule may alleviate these problems; however, determining the optimal schedule change requires an iterative process of trial and error. As the number and diversity of changes increase, it becomes necessary to notify users many times, which places a heavy burden on both users and bus operators. In addition, it is difficult to evaluate what kind of schedule is best for passengers and bus operators. Therefore, in this study, we propose a framework for simulating and analyzing various driving situations. We define a "dissatisfaction degree" based on factors related to the convenience of passengers, such as the waiting time or the congestion rate, from simulations based on actual bus traffic data. Then, we measure and evaluate the dissatisfaction degree when the driving situation changes quantitatively. Additionally, we develop a tool to confirm how operations change based on the conditions of the simulation, such as the number of buses or passengers.

1.1 Introduction

Public transport bus service is an important means of transportation for commuting, schooling and daily life. For the convenience of the passengers, it is desirable for bus service to operate on time. Public transport bus service, however, is subject to many factors that interfere with scheduled operations. The bus operation situation is easily influenced by various factors, such as traffic congestion or weather conditions. The number of passengers is also a factor that affects the delay: the more passengers need to get on and off, the more time the bus will spend at the bus stop, and the more the arrival time at the next stop will be delayed as the number of passengers increases. These factors lead to bus delays and make bus service inconvenient.

On the other hand, bus location systems have recently emerged that can easily obtain various data, such as arrival and departure times and travel locations. Using such bus location data, we have analyzed the bus delays in Aichi Prefecture, Japan, and confirmed that there are delays at specific times and places, such as during commuting time in the morning and near the main station on holidays. Naturally, bus operators have been working to resolve these delay factors and planning to operate according to a given time schedule. However, bus operators must periodically revise their schedules since the road situation and the number of passengers are constantly changing as the population increases and as changes are made to nearby facilities and the operation plans for other transportation systems. Bus operation simulations are used for this purpose.

Wang et al. considered the optimization of bus operations by using time-dependent passenger demands and traffic patterns [11]. Duzha et al. simulated public transportation to mitigate congestion in the morning and evening through cooperation between municipalities and public transport operators[5]. [3] simulated travel optimization by adjusting the departure times at specific stops to adjust bus departure times. These studies sought efficient and low-cost operation. However, it seems that these approaches show little consideration for the convenience of passengers.

In this study, we develop a simulation system to achieve both better bus operations and greater convenience for passengers using actual bus traffic data. We adopt the concept of a “dissatisfaction degree” as an index for measuring the convenience of passengers with respect to bus operations. We simulate bus operations in Okazaki City, Aichi Prefecture, where buses are delayed by 20 to 30 minutes on a daily basis due to congestion. The simulation calculates passenger appearance rates at each bus stop every hour based on passenger number data. Bus operations are simulated based on actual operation information and the numbers of passengers getting on and off. Various operation conditions are reproduced by adjusting the appearance probability of passengers and the bus arrival timing at bus stops. Then, in the area where traffic congestion occurs frequently, we evaluate how the dissatisfaction degree varies with the situation using our simulation. Furthermore, we develop a system for visualizing the simulation results and visually confirming the influence of changes in operation conditions. This research contributes (a) to the construction of a system for pursuing greater convenience for both bus operators and bus users and (b) to the efficient use of actual bus operation information and passenger number information.

1.2 Related Research

Many researchers have attempted to improve bus operations by using alternative methods to replace the optimization problem. [12] addressed the optimization problem by representing the bus network with nodes and edges, [13] studied optimal bus operation with a genetic algorithm, [6] considered optimal bus operation using a random variable to represent the bus arrival time, and [9] used an ant colony algorithm to calculate the bus delay as a stochastic value. In [10], because of the difficulty of completely optimizing bus operations, inequalities were derived to obtain suboptimal solutions as a basis for optimization. [8] studied the application of evolutionary algorithms to the operations of each bus individually.

Researchers have also attempted to reproduce bus operations using computer simulations. [3] simulated bus optimization by adjusting bus arrival intervals by adjusting the departure times of buses at specific stops. [7] and [4] simulated the construction of a bus network considering road congestion and delays due to passengers getting on and off. In [5], in cooperation with local governments and public transportation facilities, the authors studied how to eliminate congestion in the morning and evening by simulating the operation of bus routes based on the population composition of the target city and road conditions.

Moreover, research on a new form of bus operation called on-demand bus operation, in which the passenger demand is observed in real time and used to determine travel plans, was conducted in [16]. The authors of [14] and [15] are developing a system to determine the travel routes of buses in real time according to passenger demand.

In the research discussed above, optimization or simulation has been performed with the aim of mitigating congestion and delays in bus operations; however, appropriate optimization with respect to user preferences has not been done. For example, it is expected that during commuting and school hours, many people would prefer to arrive at their destinations as soon as possible even at the cost of some congestion. By contrast, those who are coming home from the shopping mall might prefer to take their time and be able to find a seat when boarding the bus. Therefore, in this study, in addition to improving the efficiency of operations from the bus operator's perspective, we also consider optimization from the user's perspective. Taking into account the changing seasons, different times of day, and the locations between which users require bus operations, we consider a system that will enable optimal bus operations at all times.

1.3 Proposal of the Dissatisfaction Degree for Bus Service

1.3.1 Definition of the Dissatisfaction Degree

We first present the "dissatisfaction degree", which is used to quantify passenger convenience in bus use. The "dissatisfaction degree" is defined as an index that quantifies the difference between the operations desired by passengers and the actual operations. This quantification of passenger convenience makes it possible to verify the effectiveness of various simulated bus operation schedules. In situations in which passengers' desired operations and the actual operations differ, passengers will typically use the bus under the assumption that the bus will be operated in accordance with the given timetable; thus, it is expected that any difference from passengers' desires will be caused by the actual operations being different from the timetable. The difference between the timetable and actual operations can be represented as a delay, and this delay has two components: a passenger's waiting time at the bus stop until the passenger boards the bus and the delay of the arrival time of the bus at its destination. Furthermore, if the passengers' buses are crowded, they will not be able to expect comfortable transportation to their destinations. The operation delay and level of congestion are thought to vary with various factors, such as the season, time of day, location, and weather.

This study therefore considers the "dissatisfaction degree", denoted by S, derived from the above three factors: the waiting time at the bus stop before boarding the bus, T_{wait}; the delay of the arrival time at the destination, T_{delay}; and the level of congestion, C, during boarding. We express the dissatisfaction degree by converting these factors into functions: $f(T_{wait})$, $g(T_{delay})$, and $h(C)$. Although these factors are closely related (for example, a bus that is delayed in arriving at a bus stop where passengers are waiting will also be delayed in arriving at its destination), this paper assumes that each factor is independent, and the "dissatisfaction degree" S is expressed as a combination of the values associated with each factor as expressed in the following equation. Since each factor can vary due to seasonality or time of day, each function is given a weight, ω_i:

$$S = \omega_1 f(T_{wait}) + \omega_2 g(T_{delay}) + \omega_3 h(C) \tag{1.1}$$

1.3.2 Derivation of the Functions Contributing to the Dissatisfaction Degree

Fig. 1.1 shows the derivation of each function contributing to the dissatisfaction degree. The function $f(T_{wait})$ is derived from the passenger's waiting time at the bus stop. In other words, it depends on the extent to which the actual arrival time is delayed with respect to the timetable. When the passenger must waits for 5 minutes or more because of bus delays, the value of the dissatisfaction degree increases. Since we expect that the longer the waiting time is, the greater the passenger's dissatisfaction will be, $f(T_{wait})$ is assumed to increase linearly with the waiting time. However, it is not realistic to suppose that a passenger will remain waiting for a long time during daily bus use in a region with many operating buses. The delay of the target bus is likely to be related to a delay of the previous bus, meaning that waiting passengers will be able to board the previous bus instead. Therefore, the maximum bus waiting time is set to 20 minutes, and the upper limit of the function value is accordingly fixed to 30.

The function $g(T_{delay})$ is derived from the delay of the arrival time at the destination. When T_{delay} is 5 minutes, $g(T_{delay})$ is defined as 0, and $g(T_{delay})$ is defined to linearly increase as T_{delay} increases. Finally, we derive $h(C)$ from the level of congestion on the bus. We set the level of congestion C to 1 when 50 people are on board. The seating capacity of our target buses is approximately 25 people; thus, a C value of 0.5 represents the threshold determining whether a passenger can find a seat when boarding. We expect that dissatisfaction will increase when passengers

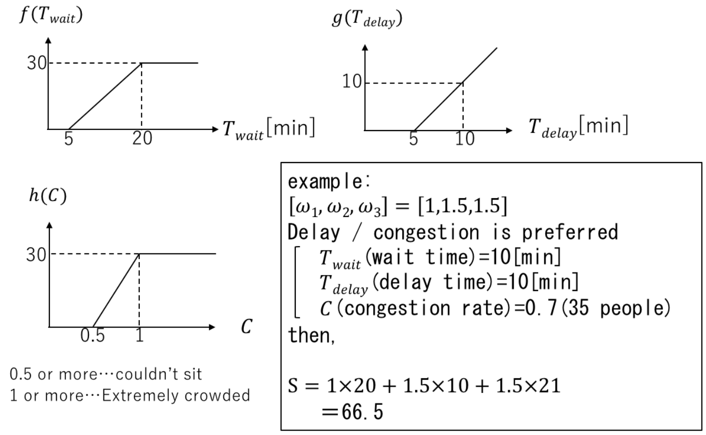

Fig. 1.1 Dissatisfaction Degree Function

are not able to sit. The more passengers are on the bus and the more crowded the bus becomes, the more dissatisfied the passengers will be. However, because there is an upper limit on the number of passengers that can ride on one bus, the upper limit on $h(C)$ is fixed to 30.

In this paper, these functions are designed using linear functions. However, various possibilities can be considered for function determination. To design a dissatisfaction degree that faithfully expresses the convenience of passengers, it is necessary to consider which functions are suitable. In this paper, we demonstrate the derivation of our dissatisfaction degree on the basis of simulations using actual data and the linear functions shown here, and we discuss the validity of the resulting values.

1.4 Simulation of the Dissatisfaction Degree

1.4.1 Outline

The dissatisfaction degree is derived from simulations based on actual bus traffic data. Our aim is to propose a method of optimizing operations by analyzing how the dissatisfaction degree varies with changes in the bus operation schedule. We repeatedly simulate changes to the bus operation schedule and derive the resulting dissatisfaction degree to observe the changes in its numerical value. The methodology applied in this research is shown in Fig. 1.2. To reproduce bus operations, we generate three kinds of agents (bus agents, bus stop agents, and passenger agents), which imitate the actual movements and characteristics of the corresponding real agents based on actual data. 1) We use three types of data, namely, bus departure data, passenger appearance rate data, and passenger destination data, to calculate

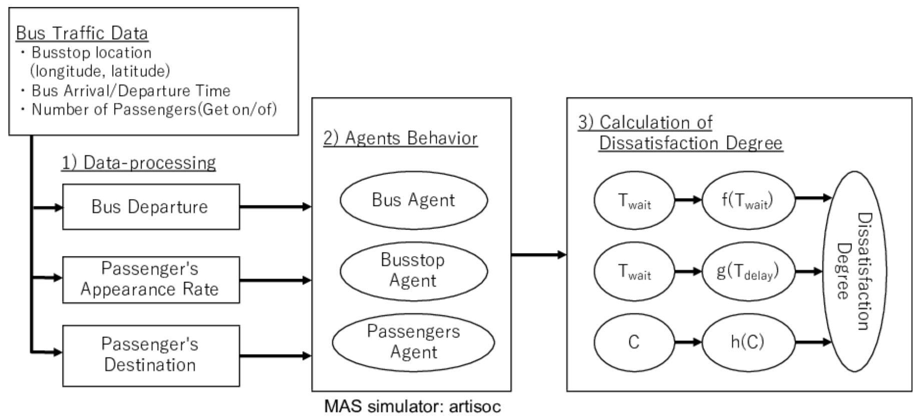

Fig. 1.2 Diagram of the Simulation Procedure

the dissatisfaction degree from simulations using actual data. 2) We simulate the behaviors of each agent based on these data. 3) We substitute the T_{wait}, T_{delay}, and C values obtained from these data into the equations presented in the previous section to calculate the value of each function.

1.4.2 Bus Traffic Data

The actual data used are bus operation data collected by Meitetsu Bus Co., Ltd., through a bus arrival information system. Their bus arrival information system records data for each bus, including the unique bus ID, the actual/scheduled arrival/departure times at each bus stop, and the numbers of passengers who get on/off at each bus stop. This study uses data from Okazaki City, Aichi Prefecture, Japan, which is a major city with a large number of buses and passengers. Meitetsu Bus Co. has 710 buses, 1539 bus stops and 523 routes in Okazaki City. The data ranges correspond to July 1-16, 2016, and from January through October 2017. In particular, we use the data collected on July 8, 2016, the day when the number of passengers was the largest between July 1 and 16, 2016.

1.4.3 Multi-agent Simulator

We develop our simulation using a multi-agent simulator (MAS): artisoc[2]. An MAS performs agent-based simulations in which an agent representing each object is placed in a defined space and each agent takes actions in accordance with behaviors determined for each step. In this study, three kinds of agents are defined: “bus stop agents”, “bus agents”, and “passenger agents”. We design the behaviors of these agents based on actual bus traffic data. The simulation outputs the data necessary for calculating the dissatisfaction degree. Then, we modify the bus operation schedule and analyze the resulting changes in the dissatisfaction degree for various operation schedules. The agents perform predetermined operations in each step. In this study, 1 step = 1 second.

1.4.4 1) Data Processing

Based on the actual data, we generate three kinds of agents: bus agents, bus stop agents, and passenger agents. The data processing described here is the procedure used to determine the behavior of each agent based on the actual bus traffic data.

1.4.4.1 Bus Departure

The bus departure data comprise the bus stop route of each bus agent and the arrival and departure times at the bus stops. The bus departure data are generated using actual bus traffic data provided by Meitetsu Bus Co., Ltd. The bus traffic data consist of the unique bus IDs, the scheduled arrival/departure times, and the actual arrival/departure times. Based on these data, we created a database consisting of the target bus IDs and the corresponding routes (the lists of bus stops visited and their order) within the target area, Okazaki City. Furthermore, we generated a reference database for the bus departure steps in the simulation from the actual arrival and departure times of each bus at each bus stop. During our simulation, each bus agent refers to these databases to determine its behavior.

1.4.4.2 Passenger Appearance Rate

The passenger appearance rate data describe the proportion of passengers appearing at each bus stop as a function of time. This rate is a value calculated from the data on the boarding/alighting of passenger agents based on the actual bus traffic data. Although we have data on the number of passengers present at each bus stop, we cannot know when each passenger arrives at the bus stop and how long the waiting time at the bus stop is. Thus, we generate the passenger appearance rates - representing when passengers visit each bus stop - through simulation.

We calculate the number of passengers at each bus stop from the actual data. To determine the timing of when each passenger appears at the bus stop before the bus arrives, passengers are stochastically generated in accordance with the upper limit on the number of passengers at the target bus stop. Each bus stop agent judges whether a passenger should appear in every step based on the passenger appearance rate data. This judgment is based on a function that returns a random number in accordance with the Poisson distribution. Since 1 step = 1 second in this study, the passenger appearance rate calculated in units of person/minute is divided by 60 to obtain the rate per second as the argument for this function.

We assume that only a return value of 0 or 1 can be obtained because the value of the argument is very small. This calculation uses the passenger number data for each bus stop and aggregates the data for every 15 minutes. Then, we divide the number of passengers for every 15-minute period by 15 to calculate the passenger appearance rate per minute. We calculate the passenger appearance rate every 15 minutes.

1.4.4.3 Passenger Destination

From the actual bus traffic data on the passengers' destinations, we determine the destination of each passenger agent. The destinations of the passengers are determined in accordance with the probabilities that passengers will get off at the various possible bus stops. Based on the data on the number of passengers getting off at each bus stop, we calculate the proportion of passengers getting off at each bus stop. The passengers' destinations are then calculated based on these proportions. For example, we consider a case in which two, three, and four passengers depart from bus stop s_1 and have destination bus stops of s_2, s_3, and s_4, respectively. The probabilities of alighting at each bus stop are then $\frac{2}{2+3+4} \approx 0.22$ for s_2, $\frac{3}{2+3+4} \approx 0.33$ for s_3, and $\frac{4}{2+3+4} \approx 0.44$ for s_4.

1.4.5 2) Agent Behaviors for Bus Operations

Based on the actual data, we generate three kinds of agents: bus agents, bus stop agents, and passenger agents.

1.4.5.1 Bus Agents

Fig. 1.3 shows the simulation flow for the behavior of the bus agents. Each bus agent moves to the next bus stop and is loaded with waiting passengers. The bus agent has the route information determining the bus stops at which it stops. Each bus also has data on the number of passengers to board and the number of passengers getting off at each bus stop. After the boarding and alighting of passengers, the bus leaves at the departure time recorded in the actual data. Then, the bus repeatedly heads for the next bus stop on its route, arrives, allows passengers to get on and off, and departs until it reaches the terminal station. The simulated arrival time at each bus stop is generated from the arrival times recorded in the actual bus departure data. We use the output of the passenger agent behavior as the data for the passengers' destinations.

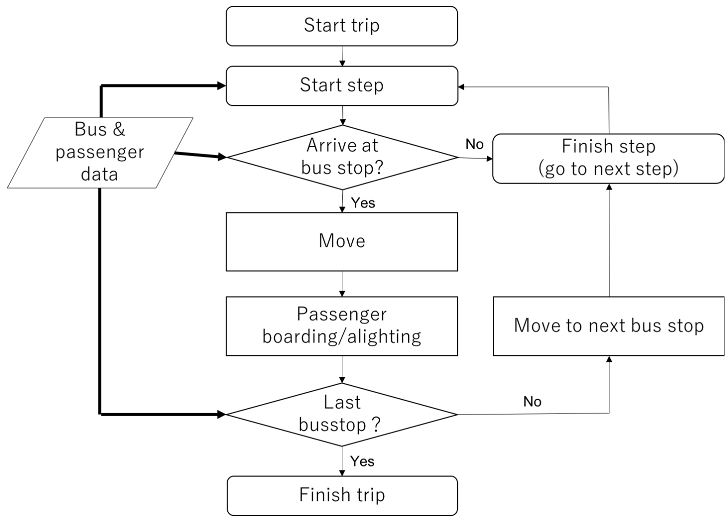

Fig. 1.3 Behavior Flow of Bus Agents

1.4.5.2 Bus Stop Agents

The role of each bus stop agent is to create the passenger agents who will board at the corresponding bus stop. The locations of the bus stop agents and the stopping buses are generated from the latitudes and longitudes of the actual bus stops and the bus route data. Each bus stop agent creates passengers in accordance with the passenger appearance rate at that bus stop. The bus stop agents are assigned individual numbers that identify the corresponding stops. These numbers are used to specify the next bus stop to which each bus should head. In addition, each bus stop agent maintains the passenger appearance rate at the corresponding bus stop for each hour as calculated from the data as a series of constant values.

1.4.5.3 Passenger Agents

Passenger agents are generated by bus stop agents. Each passenger agent has information on the destination bus stop name based on the passenger destination data. When a bus arrives at the bus stop, each passenger agent determines whether its desired destination exists on the route served by that bus. The passenger agent gets on the bus if the destination bus stop exists in the route data of the bus. The passenger agent moves along with the boarded bus. When the bus arrives at the destination bus stop, the passenger agent gets off the bus and deletes itself from the simulation field.

The simulation flow of the passenger agents is shown in Fig. 1.4. Passengers appear in accordance with the probability of appearance at each bus stop. For each step of the simulation, a random number that corresponds to the number of appearances every second (that is, the x axis of the Poisson distribution) is generated in accor-

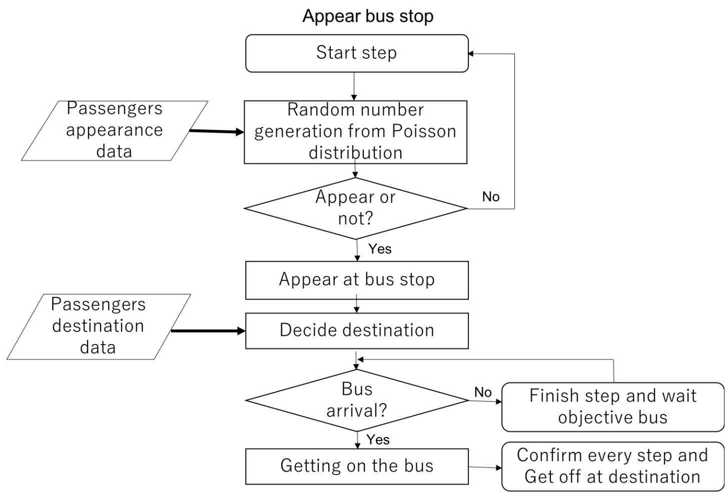

Fig. 1.4 Behavior Flow of Passenger Agents

dance with the Poisson distribution corresponding to the appearance probability per second. Since the appearance rate per second is low, almost all of the random numbers generated from the Poisson distribution will be 0 or 1. When the value is 1, a passenger appears at the corresponding bus stop.

When a bus arrives at the bus stop, the simulation judges whether each passenger's destination exists on the route served by that bus. If the route of the bus agent includes the bus stop corresponding to the passengers agent's destination, that passenger agent gets on the bus. When the bus agent arrives at the destination bus stop, the passenger agent gets off the bus. The simulation records the times at which each passenger gets on and off the bus.

1.4.6 3) Calculation of the Dissatisfaction Degree

We describe the procedure for calculating the dissatisfaction degree from the behavior of each agent. The simulation outputs the appearance times of passengers waiting for a bus at each bus stop from the behaviors of the passenger agents. The difference between the appearance time and the arrival time of the bus is T_{wait}. To calculate $f(T_{wait})$, we substitute T_{wait} into:

$$f(T_{wait}) = \begin{cases} 2T_{wait} - 10 & (T_{wait} \leq 20) \\ 30 & (T_{wait} > 20) \end{cases} \tag{1.2}$$

Furthermore, the simulation records the time at which each passenger agent gets off at the destination bus stop. The difference between the scheduled arrival time and the agent's alighting time is T_{delay}. To calculate $g(T_{delay})$, we similarly substitute T_{delay} into:

$$g(T_{delay}) = 2T_{delay} - 10 \tag{1.3}$$

Each bus agent holds data on the number of passengers on the bus. Let C be the number of passengers when the target passenger agent boards; to calculate $h(C)$, we substitute this value into:

$$h(C) = \begin{cases} 60C - 30 & (C \leq 1) \\ 30 & (C > 1) \end{cases} \tag{1.4}$$

Finally, we calculate the dissatisfaction degree S of each passenger by substituting $f(T_{delay})$, $g(T_{wait})$, and $h(C)$ into equation (1.1).

1.4.7 Visualization Tool

Although this study aims to quantify the convenience of passengers and use the resulting dissatisfaction degree to optimize the bus operation schedule, it is also critical to consider the analysis of bus operations from the viewpoint of the bus operator. Hence, we have developed a visualization tool, called Harmoware-VIS[1], to present the result of the proposed simulations. Harmoware-VIS is based on deck.gl[2], a WebGL-based big data visualization framework developed and published by Uber. The deck.gl framework can perform the analysis and drawing tasks based on a GPU implementation and can combine multiple layers. Using this multi-layer capability, we can visualize various data, such as the behavior of passengers at each bus stop or the weather conditions, in addition to the bus operation output from the simulation for the purpose of observing the interactions between bus operations and other factors.

Fig. 1.5 shows the Harmoware-VIS interface displaying bus traffic data and the number of passengers at each bus stop. In this figure, light purple circles represent bus stops, and green, yellow and red circles represent buses. The different colors represent different degrees of delay for the buses. When a bus is delayed, the color of the circle representing it changes. The circle is red when the bus is delayed and is green when it is operating on time. The data are described in a json file, and the display is updated according to the passage of time. The vertical bar at each bus and bus stop shows the corresponding number of passengers. The bar at each bus stop indicates the number of people waiting to get on at that time.

[1] Harmoware-VIS: https://github.com/Harmoware/Harmoware-VIS

[2] deck.gl: https://deck.gl/

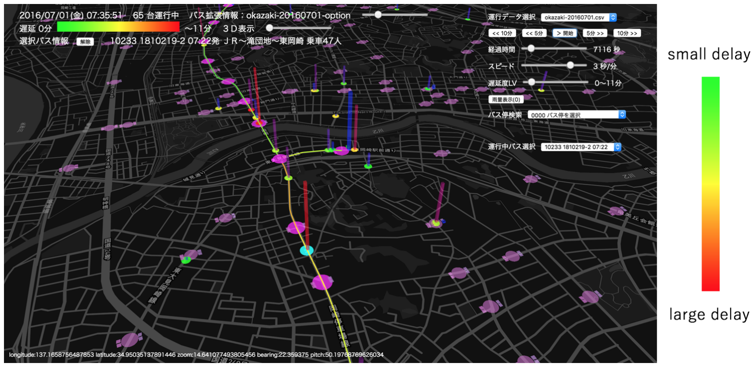

Fig. 1.5 Bus Operation Visualization Using Harmoware-VIS

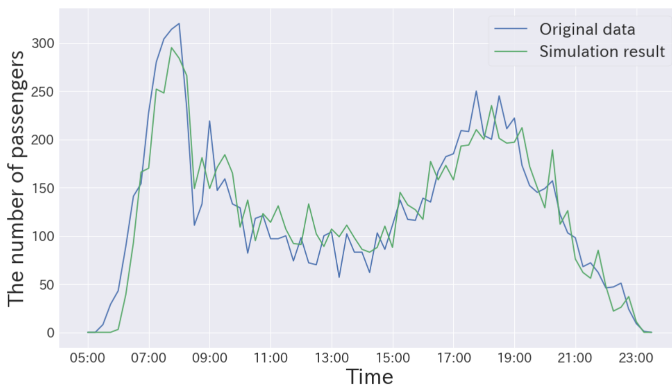

Fig. 1.6 Simulation Result of Number of Passengers at All Busstops

1.5 Simulation Result

In this section, we will explain the results of our simulations. The simulation results obtained using artisoc are shown. We carried out simulations with fixed passenger appearance rates and varying bus operation schedules. The passenger appearance rates were fixed to those observed on July 8, 2016, and the simulations were conducted by varying the bus operation schedules to correspond to those observed from July 4 to 8, 2016. The simulation results can be presented in two forms: the change in the number of passengers over time and the change in the number of passengers waiting to board at a bus stop over time.

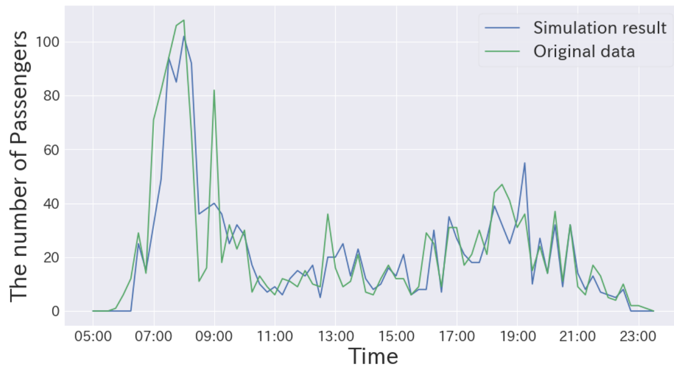

Fig. 1.7 Simulation Result of Number of Passengers at Busstop:"Okazaki station"

1.5.1 Time Transition of the Number of Passengers

The transition of the number of passengers over time is shown in Fig. 1.6. The horizontal axis represents time, and the vertical axis represents the number of passengers by showing the number of people who boarded every arriving bus at all stops. Notably, the granularity of a representation of all rides at every time point is too fine for good visibility; therefore, the aggregated number of passengers for every 15-minute period is shown instead. In this way, it can be seen that the simulated numbers of passengers are close to the actual data. The correlation coefficient between the actual data and the simulation result is 0.94. Next, a graph showing the change in the number of passengers over time at a given bus stop is shown in Fig. 1.7. It can be seen that even for a single bus stop, the change in the number of passengers can be reproduced with a quality similar to that achieved for the bus system as a whole.

1.5.2 Time Transition of the Number of Passengers Waiting for Boarding

The transition of the number of passengers waiting to board at all bus stops over time is shown in Fig. 1.8. It can be seen that the passenger volume is concentrated during commuting hours, whereas the curve is more gentle in the afternoon when various people are riding. It seems that some degree of reproducibility is obtained. A more detailed examination of the degree of reproducibility will be addressed in future work. In addition, these data were obtained by excluding the changes at the Higashi Okazaki and Okazaki Station stops. The results were not accurate when these stops were included. These stops are the main stops in Okazaki City, where people with a wide variety of destinations gather. Since the destination probabilities of the passengers run throughout the day, there is a possibility that a passenger may

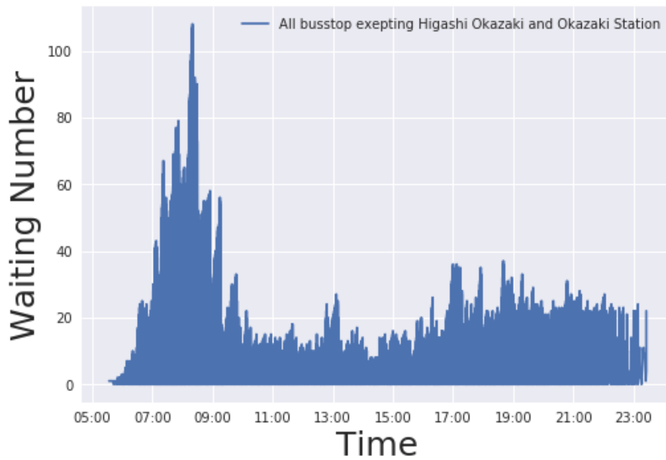

Fig. 1.8 Time Transition of the Number of Passengers Waiting for Boarding Excepting "Higashi Okazaki" and "Okazaki Station"

appear even though there is no bus scheduled that is heading towards that passenger's destination at that time.

1.5.3 Simulation Results for Different Operation Dates

Fig. 1.1 shows the results of simulations with the same passenger appearance rates and varying operation schedules. In the current method of calculating the dissatisfaction degree, when the level of congestion is 0.5 or less, the dissatisfaction degree due to congestion becomes 0. The average level of congestion is 0.39 - 0.48; therefore, the influence of this index on the overall dissatisfaction is considered to be low. Consequently, the main factors affecting dissatisfaction are delay and waiting time. On Saturdays and Sundays, the number of buses is decreased compared to that on weekdays, and the waiting time is correspondingly increased; however, the bus delays are simultaneously reduced. As a result, the dissatisfaction degree remains approximately the same. Delay is the main reason why the dissatisfaction degree on the 8th is found to be especially large; indeed, the bus delay on this day was approximately 1.7 times the delay on other days (including weekdays), so it seems that the influence of this factor is clear.

Table 1.1 Simulation Result (Passenger Appearance Rate: July 8, 2016, Bus Operation: from July 4 to 8, 2016)

	July 4 (Mon)	July 5 (Tue)	July 6 (Wed)	July 7 (Thu)	July 8 (Fri)	July 9 (Sat)	July 10 (Sun)
Level of Congestion	0.40	0.39	0.40	0.39	0.40	0.48	0.48
Wait Time [s]	502	485	500	500	489	528	539
Delay Time [s]	265	268	216	254	443	327	185
Dissatisfaction Degree	59.1	58.7	57.7	58.7	63.3	61.0	58.1
Number of Buses	415	415	415	415	415	372	372

1.5.4 Simulation Result of Various Passengers Rate

Then, we show the results of the simulation, changing the number of passengers. The simulation result using the bus operation condition on July 6, and the passengers appearance rate from from July 4 to 8, 2016 is shown in Table1.2 A). The bus operated on the same schedule on weekdays and on weekends. The number of passengers of the targeted area were 483, 950, 878, 947, 908, 367, 476 passengers, from July 4 to 8, respectively, passengers on July 4, 9, 10 were small. Therefore, the dissatisfaction degree on July 4, 9, 10 was calculated especially low. The maximum congestion rate was 0.7.

This paper defines three functions: $f(T_{delay})$, $g(T_{wait})$, $h(C)$ for calculating the dissatisfaction degree. We evaluate these kinds of functions by manipulating the combination of functions, as to whether these functions are necessary or not. The Table 1.2 B) is a simulation result performed using only $f(T_{delay})$ and $g(T_{wait})$ in equation (1.1). The dissatisfaction degree on this condition shows dissatisfaction only by the bus arrival time delay and the delay to the destination. The dissatisfaction degree on July 4 and July 6 were 19.2, 20.9, which were not so much difference. However, each maximum value of the congestion rate is 0.5, 0.7. The number of passengers on July 4 was crowded to the extent that passengers could sit, on the other hand, the passengers on July 6 were in a situation where some passengers could not sit. It seems that there is a difference in the situation of passengers on the bus on the 2 days, although the differences could not be properly expressed by not using $h(C)$.

Furthermore, Table 1.2 C) is a simulation result performed using only $f(T_{delay})$ and $h(C)$ in equation (1.1). Though we can observed delay, all dissatisfaction degree was equal. It was impossible to adequately represent a decline in convenience to passengers due to delay. Dissatisfaction degree could not adequately represent a decline in convenience of passengers due to delay.

Table 1.2 D) is a simulation result performed using only $g(T_{wait})$ and $h(C)$ in equation (1.1). The simulation using these two functions is almost the same as A), however, there was a difference from A) only on July 5. The arrival time to the destination is related to the waiting time for bus. Thus the longer the waiting time, the higher the possibility that the arrival time will be delayed. However, due to traffic congestion on the way to the destination, the arrival time may be delayed,

Table 1.2 Simulation Result of Various Passengers Rate at All Busstops

	July 4 (Mon)	July 5 (Tue)	July 6 (Wed)	July 7 (Thu)	July 8 (Fri)	July 9 (Sat)	July 10 (Sun)
A) $f(T_{delay})$, $g(T_{wait})$, $h(C)$	58.4	61.4	61.3	60.7	61.1	59.6	59.6
B) $f(T_{delay})$, $g(T_{wait})$	19.2	21.0	20.9	19.7	20.4	19.5	20.5
C) $f(T_{delay})$, $h(C)$	45.0	45.0	45.0	45.0	45.0	45.0	45.0
D) $g(T_{wait})$, $h(C)$	58.4	61.5	61.3	60.7	61.1	59.6	59.6

Table 1.3 Simulation Result of Various Passengers Rate at Terminal Busstops

	July 4 (Mon)	July 5 (Tue)	July 6 (Wed)	July 7 (Thu)	July 8 (Fri)	July 9 (Sat)	July 10 (Sun)
A) $f(T_{delay})$, $g(T_{wait})$, $h(C)$	56.7	61.4	61.1	60.4	60.2	59.6	60.5
B) $f(T_{delay})$, $g(T_{wait})$	17.1	21.1	21.5	19.3	20.0	18.8	20.3
C) $f(T_{delay})$, $h(C)$	45.0	45.0	45.0	45.0	45.0	45.0	45.0
D) $g(T_{wait})$, $h(C)$	56.7	61.4	61.1	60.4	60.2	59.6	60.5

and dissatisfaction degree simulation including $f(T_{delay})$ can correspond to various situations.

Table 1.3 shows the result of calculating the dissatisfaction degree by extracting only the bus heading near the terminal station, which has a particularly large number of passengers in the target area. We fixed the bus operation to July 6, and simulated the passenger appearance rate from July 4 to 8, 2016. Thus the results are similar to Table 1.2, result on July 4is 56.7, which is lower than 58.4 of Table 1.2 A). Passengers heading to terminal stations are considered to be commuters on weekdays or train passengers on weekends. It seems that the dissatisfaction degree on July 4 is low, because the passengers are fewer and delay is less than other busstops.

1.5.5 Simulation Result for Various ω_i

We show the simulation results by changing ω_i to various values. In previous section, the simulations were performed using weights of $\omega_i = [1, 1.5, 1.5]$. However, we believe that the value of ω_i will take various values depending on the characteristics or conditions of passengers. That is, the possible values of ω_i can be changed according to the situation in which it is in a hurry condition such as commuting to school or office. In shopping situation, passengers will tolerate some delay but would like to get on the empty bus as possible. It is also thought that the elderly people will give priority to sitting when taking a bus from delay. Thus, we assume the several combination of ω_i for various situations.

The simulation results with the passengers appearance rate and operation condition of July 6 are shown in Table 1.4 and 1.5. Here, i) is a set of ω_i for commuters, $\omega_i = [1.5, 1.5, 0.5]$. This ω_i includes the factors: T_{delay}, T_{wait} of functions $f(T_{delay})$,

Table 1.4 Simulation Result for Various ω_i(To Terminal Station)

	Weekday (7:00-10:00)	Weekday (10:00-12:00)	Weekday (13:00-16:00)	Weekends (13:00-16:00)
i) Commuters	40.0	44.3	37.4	46.9
ii) Elders	62.2	64.5	60.0	66.3
iii) Others	47.2	49.5	45.0	51.2

Table 1.5 Simulation Result for Various ω_i(To Hospital)

	July 4 (Mon)	July 5 (Tue)	July 6 (Wed)	July 7 (Thu)	July 8 (Fri)
i) Commuters	38.1	31.7	35.5	49.2	40.3
ii) Elders	60.4	56.1	58.7	67.8	61.8
iii) Others	45.4	41.1	43.7	52.8	46.8

$g(T_{wait})$ and $h(C)$, that is, the definition that the delay greatly affects passengers' dissatisfactions. ii) is a set of ω_i for the elderly people, $\omega_i = [1.0, 0.5, 1.5]$. We thought that the waiting time for bus and bus congestion rate - T_{wait} and C - have a great influence on dissatisfaction. iii) is a set of ω_i assuming a time-constrained situation such as shopping, $\omega_i = [1.0, 1.0, 1.0]$.

Table 1.4 shows the simulation results using various ω_i. We simulate the dissatisfaction degree, extracting the data of passengers heading for busstop near two terminal stations in the target area. We compare the dissatisfaction degrees with the timezone of Weekday (7: 00-10: 00), Weekday (10: 00-12: 00), Weekday (13: 00-16: 00), Weekends (13: 00-16: 00) for i), ii), iii). In all the time zones of Weekday and Weekends, ii) Elders' dissatisfaction degree got higher than i) Commuters'. For the passengers heading to the terminal stations, the extracted timezone has particularly commuters, the dissatisfaction degree was calculated large for ii) Elders. For Weekday (13: 00-16: 00) not commuting time, i), ii), iii) all got a lower dissatisfaction degree.

Table 1.5 is the result of extracting passengers heading to five hospitals in the target area. We extracted the data of 8:00-12:00, as to hospital business hours. Especially ii) Elders' dissatisfaction degree is high on July 4, which is crowded with passengers heading to hospital on the first day after the holidays, thus possibly the dissatisfaction degree has increased. On July 7, the dissatisfaction degree is higher in i), ii), iii). The simulation results that the number of passengers increases on a specific day of the week and the dissatisfaction degree increases. ii) Elders' dissatisfaction degree was also particularly high, whereas, the dissatisfaction degree of i) Commuters and iii) Others was calculated relatively low.

1.6 Conclusion

In this study, for the optimization of bus operations through simulation, we have proposed the concept of the “dissatisfaction degree”, which is an index that varies with the operation evaluation criteria for each user. By doing so, we aim not only to improve the efficiency of operations from the bus operator’s point of view but also to ensure comfortable bus operations from the perspective of each passenger. Using actual transportation data provided by Meitetsu Bus Co., Ltd., we constructed a simulation to reproduce bus operations using the MAS artisoc. We confirmed that the simulation performed correctly by approximating the number of passengers per hour, achieving a correlation coefficient of 0.94 between the simulation results and actual operation data. In addition, visualization software that displays on a map the number of people waiting to board at each bus stop and the number of passengers on each bus has been made available by means of the visualization library BusDataVisualizer using deck.gl.

In future work, a clear definition of the dissatisfaction degree should first be developed. It will be necessary to examine the correlations of factors such as location and time with operation times and congestion levels and to further investigate the influence of operation time and congestion level on the overall dissatisfaction degree. Next, it will be necessary to calculate the passenger destination probabilities with respect to time to achieve more accurate probabilities and then to examine the extent to which the numbers of people waiting to board over time are accurately reproduced. Moreover, in the current simulation, the bus behavior is completely determined over time, and there is no model for modifying the delays during the simulation. Therefore, it will be necessary to address this shortcoming. Then, we will examine the resulting influence on the dissatisfaction degree when the operation schedule is changed.

In addition, we intend to further develop the visualization tool in the future. With the current specifications, it is not possible to compare multiple operation schedules simultaneously on one screen, so it will be necessary to implement the ability to review various simulation results at the same time. The tool should also provide the ability to simultaneously review various types of information, such as delay logs, which is a subject to be studied in the future.

The purpose of visualizing the simulation results is to visually confirm how the passenger flow changes when the simulation conditions change. The simulation conditions considered are the bus operation times, the number of operating buses, and the passenger appearance rates. We will make various modifications to ensure the faithful reproduction of various driving scenarios (such as different days of the week and seasons) and to improve the definition of the dissatisfaction degree.

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